

Alberizzi, Andrea; Di Barba, Paolo; Ziel, Florian

Article — Published Version

Agent based modeling for intraday electricity markets

OPSEARCH

Provided in Cooperation with:

Springer Nature

Suggested Citation: Alberizzi, Andrea; Di Barba, Paolo; Ziel, Florian (2024) : Agent based modeling for intraday electricity markets, OPSEARCH, ISSN 0975-0320, Springer India, New Delhi, Vol. 62, Iss. 1, pp. 178-197,
<https://doi.org/10.1007/s12597-024-00805-w>

This Version is available at:

<https://hdl.handle.net/10419/323634>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<http://creativecommons.org/licenses/by/4.0/>



Agent based modeling for intraday electricity markets

Andrea Alberizzi¹ · Paolo Di Barba¹ · Florian Ziel²

Accepted: 12 June 2024 / Published online: 24 June 2024
© The Author(s) 2024

Abstract

In recent years, the strong growth of renewable energy sources has led to considerable instability in the electricity markets. As a consequence, this has increased trading activities in the continuous intraday market, especially close to delivery. This work presents an agent-based model that is able to reproduce the continuous market evolution, distinguishing players in dispatchable and non-dispatchable power plants and analyzing the behavior and interactions between them. All players behave rationally, trying to maximize their revenues and minimize imbalances. The results show that the model is able to reproduce the main characteristics of the continuous intraday electricity market, such as the price path strongly dependent on internal and external information, such as the wind production forecast, possible outages, an increase in order arrival towards the end of the trading session and weak market efficiency. The strategies assigned to each agent have been formulated taking into account statistical analyses of historical orders placed during continuous trading in different European bidding zones. The analyses have been carried out in a scenario composed of thermal plants with different marginal costs and wind agents, but the flexibility of the model gives the possibility to study many different scenarios.

Keywords Continuous trading · Renewable energies · Power system · Bidding strategy

✉ Andrea Alberizzi
andrea.alberizzi01@universitadipavia.it

Paolo Di Barba
paolo.dibarba@unipv.it

Florian Ziel
florian.ziel@uni-due.de

¹ Industrial Engineering, University of Pavia, Pavia, Italy

² Economy, University of Duisburg-Essen, Essen, Germany

1 Introduction

In most European countries, the majority of energy trading occurs on spot markets that are divided into day-ahead (DAM) and intraday (ID) markets [1]. The ID session allows energy agents to mitigate imbalances and avoid high penalty costs. With the increased use of intermittent resources, such as wind and solar, forecasting power production has become more difficult, and the use of the ID market has become crucial to minimize imbalances [2]. As a result, the volume of energy exchanged on the ID market has grown significantly in recent years, with Germany and France showing increases of 18% and 38% respectively from 2019 to 2020 [3]. To improve market integration and coupling, the Agency for the cooperation of energy regulators (ACER) [4] has launched the single intraday market coupling (SIDC) project, which allows ID market participants from most European countries to trade electricity on a common order book up to 1 h before delivery time [5]. The project includes continuous trading even in countries that have historically used the auction system, like Spain [6]. Consequently, researchers have focused on how players behave to maximize profits and minimize imbalances, making algorithmic trading strategies highly relevant for studying balancing actions.

Agent-based models are well-developed systems for simulating energy market trading and studying the behavior of market participants and their interactions [7] [8]. Some examples are the electricity market complex adaptive system (EMCAS) [9], the national electricity market simulation system [10] and the agent-based modelling of electricity system [11] but they do not really consider the operational market rules of the continuous intraday market. Different strategies for trading in continuous have been implemented and improved from the ZI strategy [12] in which traders submit random bids only with a budget constraint to the adaptive-aggressiveness strategy (AA) [13] in which traders adapt their behavior following different market conditions deciding if maintaining a passive or aggressive attitude on submitting orders. Meanwhile, other strategies have been adopted like the ZIP strategy [14] the GD strategy [10] and the GDX strategy [15] For many years the AA algorithm has been the best strategy able to replicate the continuous market but in [16] it is stated that it can be outperformed by other algorithms when tested across a big number of market sessions.

Existing models in the literature, while proficient in depicting the continuous trading energy market, often overlook two critical aspects. Firstly, they fail to account for external events such as wind and solar forecasts, which have become integral for predicting the available energy supply [17]. Secondly, these models lack a consistent method for reproducing a continuous time frame, relying instead on a discretized approach.

Our work aims at creating an agent-based algorithm able to represent the continuous trading of agents in a more realistic scenario considering internal and external factors for a properly agents strategy. First of all the SIDC trading mechanism is perfectly replicated by reproducing a limit offers book [18] able to store all orders with a price-time merit order and to couple the orders following

the continuous trading matching algorithm based on the first-come-first-served rule [19]. Secondly, to successfully represent the agent's behavior, players get the more realistic behavior as possible trying to maximize their revenues and minimize the unbalances [20]. Agents are also divided into dispatchable and non-dispatchable power plants each one characterized by a reasonable trading strategy strictly correlated to the technology of the power plant and to the external and internal factors of the market sessions. The entire simulation employs an innovative approach to replicate continuous interactions among agents, departing from the traditional discrete time-frame method.

The paper is structured as follow: Sect. 2 describes the intraday market focusing on continuous trading and underlines the main characteristics resulting from bidding in continuous throughout statistical analyses of historical market data. In Sect. 3, a detailed description of the proposed agent-based model is presented. Section 4 highlights the results achieved by the algorithm implemented while conclusions are explained in Sect. 5.

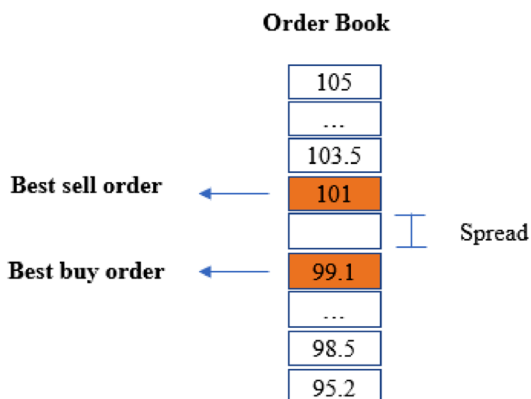
2 Intraday market

In this section, firstly the intraday market is described in detail then the relevant aspects of continuous market characteristics are highlighted.

2.1 Market description

In Europe, the electricity spot market for hourly delivery products is divided into the day-ahead and intraday sessions set up in a temporal sequence [21]. The day ahead market is coupled among the majority of European countries and is based on a two-sided auction. There the market participants can submit bids for the sell and buy side until 12am. CE(S)T of the previous day (d-1) of the delivery for all 24 hourly delivery products (Fig. 1).

Fig. 1 Assumed position of orders stored in the order book



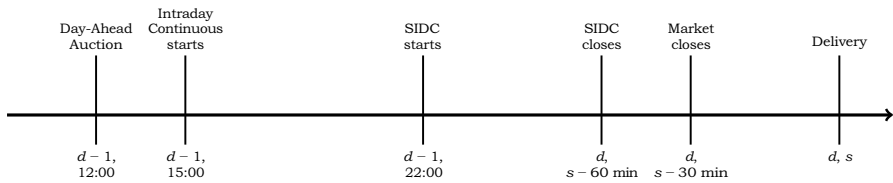


Fig. 2 The daily routine of a typical European electricity spot electricity market. d corresponds to the day of the delivery and s corresponds to the hour of the delivery

3 h after the day-ahead market closing, the intraday market starts (see Figure 2). Here, thanks to the single intraday market coupling (SIDC), agents of all European bidding zones have the possibility to exchange energy until 1 h before the delivery time using the continuous trading mechanism.

But since different studies such as [22] show that a hybrid model composed of a combination of auctions and continuous trading is more efficient in terms of liquidity, price volatility and market depth some countries decided to introduce different number of auctions besides continuous trading. As well as in the day-ahead market auction, during intraday auctions agents can submit orders during a certain time-frame. Once the trading time closes, all bids are aggregated and create the supply and demand curves. The intersection of the two curves forms the so-called system marginal price that is the uniform price of the auction market session. This system provides perfect price transparency but does not allow market participants to adjust their position after the gate closure of the auction session. Still, the continuous intraday trading is the most important option, and also the only option in important countries like France or Germany. Trading starts at 15.00 of $d-1$ for hourly products and at 18.00 of $d-1$ starts the cross-border trading within the SIDC platform. Players can exchange energy in the Single Intraday market until 1 h before the delivery time and even closer to the real time in some market bidding zones (i.e. in Germany ID market players can trade until 5 min before the delivery). Here, agents can submit bids at any time until 1 h before the real-time of delivery and they can trade among all European countries as long as there is enough transmission capacity available. All orders are stored in the shared order book (SOB) while the capacity is collected and updated in the capacity management module (CMM) and the information about concluded trades are available in the shipping module (SM). Order's matching is a deterministic process that follows the conclusion of trading. To obtain a match, orders must present the same contract referred to that specifying the product (hourly) and the delivery time and coming from the opposite side (sell/buy). The matching procedure follows the first-time first-served rule by which a transaction occurs immediately when the price of an entry buy (sell) order is higher (lower) than the price of a sell (buy) order already stored in the order book [23]. The matched price corresponds to the price of the order already presents in the book. Matching takes place always at the best possible price so for instance, a buy order will find a match with the cheapest sell order presented in the order book while a sell one will find a match with the most expensive buy order existing in the book.

Once an order is executed it can generate multiple matches until its quantity reach zero or there are no more conditions for other matches. If a submitted order doesn't find a match it can be stored in the order book. Order storage follows the price-time merit order, so sell (buy) orders are stored from the lowest (highest) to the highest (lowest) price as shown in Fig. 1.

If two orders coming from the same side present the same price, the first order submitted gets priority. Agents can apply particular execution restrictions to an order submitted such as:

- Fill or Kill (FOK) restriction, by which the order will be deleted by the system if it is not immediately entirely matched
- Immediate or Cancel (IOC) restriction, by which the order must be executed immediately even partially and the remaining quantity will be deleted by the system
- All or Nothing (AON) restriction by which the order remains in the order book but can be executed only entirely [24]

Agents can also decide to submit the so called 'market orders' which are executed immediately at the best price available in the market. In the following section, the most significant continuous trading market characteristics are explained.

2.2 Market characteristics

Different studies have been led so far on historical orders submitted by agents during the continuous trading sessions of the single intraday market coupling and many considerations has been carried out about the main aspects of this type of energy market. First of all, even if traders can trade continuously from the day before the delivery time, they use this market mainly during the last hours available for submission. This behavior stated in [2] is proved in [25] with Figure 3.

A second relevant aspect is the type of orders and prices submitted by different agents based in their technologies. The agents are divided into two categories such as dispatchable (i.e. thermal) and non-dispatchable (i.e. wind) power plants, researches highlighted that dispatchable players submit regular orders around their marginal costs MC deciding if buy or sell energy comparing its production costs to the current market price MP . In particular if $MC > MP$ they submit buy offers to buy energy at a cheaper price instead of producing it at higher costs otherwise they submit sell offers to gain higher revenues. An important consideration is that even if a power plant is accepted to bid in the day-ahead market, it will not sell its entire capacity but it will keep some percentage of energy available to sell during the continuous trading if market conditions can increase its profits. However non-dispatchable players, without any production costs, submit mostly orders at the best market price so at P_{\min} for sell orders and P_{\max} for buy orders because they need to adjust their position after a new forecast production and they want to be sure to enter in the market. Dispatchable power plants are also willing to leave the orders in the order book until the end of the market session because an eventual transaction will

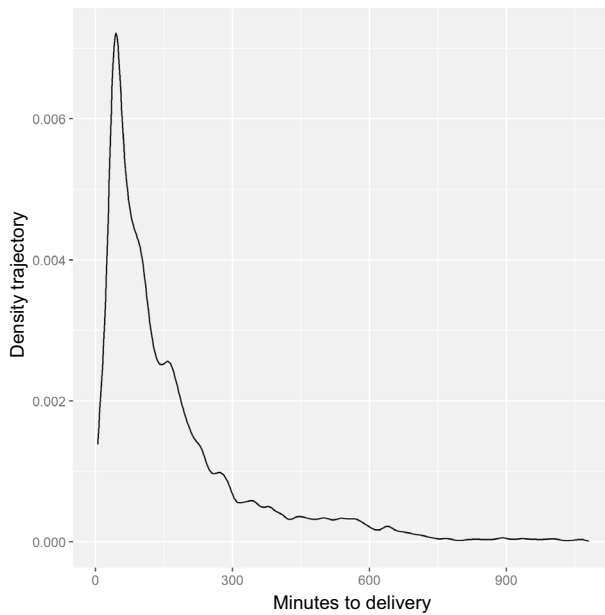


Fig. 3 Density trajectory refers to all orders submitted from 2020-01-01 to 2020-12-31 for delivery products across all 24 h of the market

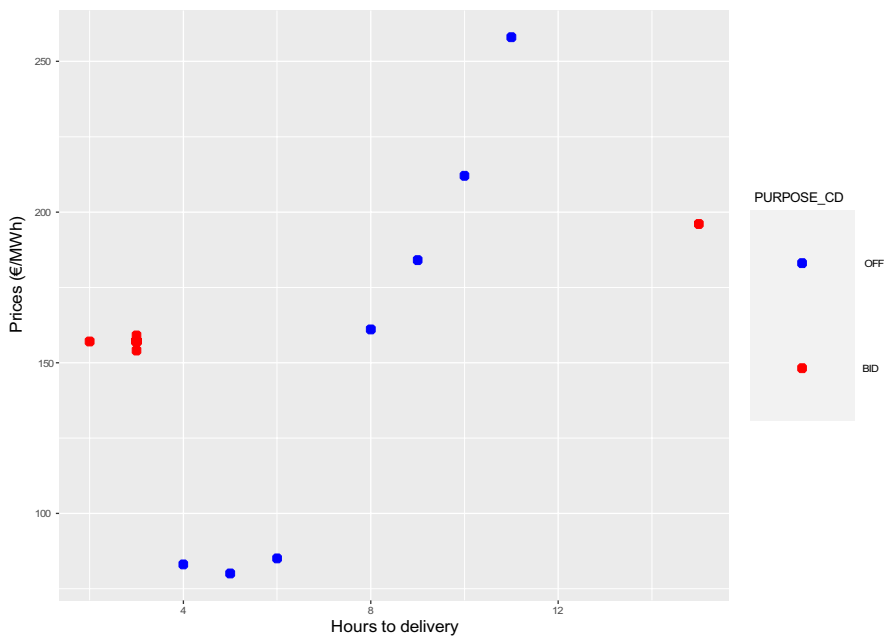


Fig. 4 Prices of orders submitted by a thermal power plant during a session of continuous trading in the Italy south bidding zone

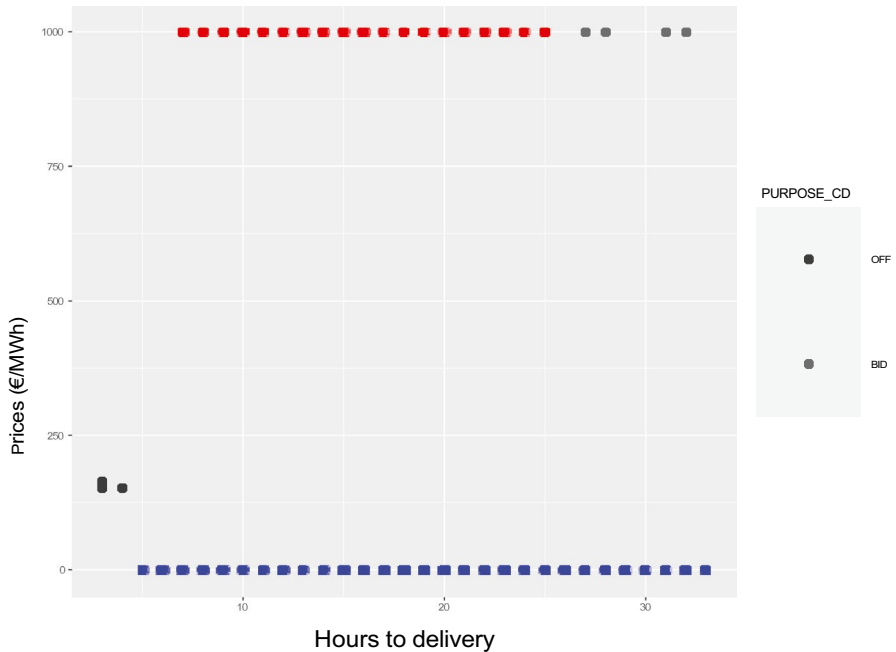


Fig. 5 Prices of orders submitted by a wind power plant during a session of continuous trading in the Italy south bidding zone

provide revenues, while non-dispatchable power plants retire immediately the order if no matches occur to don't sell (buy) energy effectively at the minimum (maximum) market price. This behavior is proved in Figure 4 and 5 where the price of orders submitted by a thermal and a wind power plant during a session of continuous trading in the Italy south bidding zones is shown.

Moreover, it is also stated that an increasing of natural resources, such as wind or solar, during the intraday session decrements the market price compared to the system marginal price that comes out from the day ahead market while a decrease of natural resources increments the current market price. The reason of this price fluctuation results from the fact that when renewables forecast a better power production, they can sell the excess of energy at the lowest market price and so thermal power plants decide to buy energy from them avoiding production costs. On the contrary, when renewables forecast a decrease of production they must buy energy at any price to don't incur into penalties imbalances and so the most expensive thermal power plants can sell their energy with high prices.

Additionally, we want to mention that the continuous intraday market shares not only design characteristics of financial markets but also share one important property. This is market efficiency. Several recent articles show that the European intraday markets are efficient, or extremely close to efficiency, see e.g. [26], [27] In mathematical terms this means that the price process satisfies the martingale property, i.e. $E[P_{t+h}|F_t] = E[P_t|F_t]$ for $h > 0$. Thus, an appropriate agent-based electricity market model should reflect this behavior.

3 Agent based model

Our agent based model shall be able to cover realistic behavior seen on the market. We assume only rational agents.

We consider N agents. We assume that there are two groups of agents, $N_{\text{conventional}}$ fuel powered and N_{RES} renewables, i.e. $N = N_{\text{conventional}} + N_{\text{RES}}$. Thus, we ignore agents which hold portfolios of those physical assets. *For non-dispatchable agents, we opted to simulate an energy production forecast for wind power plants by replicating a specific function described in Chapter 4.1 to form an energy production forecast curve. Currently, solar power plants are excluded from this simulation; however, their strategy would mirror that of the wind agent, contingent upon the solar forecast instead of the wind forecast. Consequently, incorporating a solar production forecast is not anticipated to significantly alter any results in this simulation.* Since the ID market starts after the closing of the day-ahead session, at the beginning of the simulation, the supply–demand aggregation curve generating form the day-ahead auction is set up in order to point out which generators have been accepted in the market, which one have been excluded and which is the system marginal price. We assume that the n -th agent has a quantity $q_{t,n}$ that is already sold/bought at time t , often this referred as traded quantity. We consider the convention that positive quantity represents sold volumes and positive quantity refer to bought volumes. Thus, positive $q_{t,n}$ values should be associated with the generation of power and negative ones with consumption. For notation convenience, let $\mathbf{q}_t = (q_{t,1}, q_{t,2}, \dots, q_{t,N})$ the traded quantity vector at time t . Further we introduce with $q_t^{\min} = (q_{t,1}^{\min}, q_{t,2}^{\min}, \dots, q_{t,N}^{\min})$ and $q_t^{\max} = (q_{t,1}^{\max}, q_{t,2}^{\max}, \dots, q_{t,N}^{\max})$ the minimum and the maximum quantity that can be delivered/consumed given the maximum flexibility of the n -th without going into imbalance. For a 100 MW conventional power plant that has at time t still all flexibility to decrease the output to 0 this is $q_{t,n}^{\min} = 0$ and $q_{t,n}^{\max} = 100$. For fluctuating renewables.

like wind and solar is $q_{t,n}^{\max}$ usually a random variable due to unknown weather conditions. However, as pointed out by [28], risk-neutral agents optimize profit by bidding the median of the underlying distribution. We will adopt this behavior here as well. Note that if an outages of a conventional power plant happens, we get $q_{t,n}^{\max} = 0$. Thus, under consideration of outages also $q_{t,n}^{\max}$ is a variable for fuel power plant that refers to a planned outage. If we consider a retailer agent, we have $q_{t,n}^{\max} = 0$ and $q_{t,n}^{\min}$ as the volume of the load profile of the asset

For the agent-based model we will assume for simplification (first) that only small minimal units are traded by the market participants (e.g. 1 MW). Thus, if an agent wants to sell or buy large volumes he has to place multiple orders. This, restriction is reasonable for efficient markets as multiple small trades have smaller volatility than one large one with the same volume. Still, this assumption could be easily relaxed but does not substantially change the results.

Due to the continuous trading nature theoretically, all agents could do an action every tiny time unit (e.g. milli seconds and even below). However, for modeling purposes, we assume that every agent checks if he may perform an action

on the market (e.g. submitting an order) just at specific *potential* action times. We denote the potential action times by $\tau_{s,n}$ for the s -th potential action of the n -th agents. We consider $\tau_{0,n} = 0$ as initialization action. This is when every agent submits an initial bid to fill the order book when trading starts. We assume that the initial orders are based on the day-ahead market results. So all generators that have been accepted to bid in the day-ahead session fill the order book with buy orders, while excluded generators fill the order book with sell offers. But since, at the beginning of the session, wind agents are perfectly balanced, only thermal power plants fill the order book because they still have some capacity left available to sell or to buy. The initial market price corresponds to the system marginal price coming from the day-ahead auction result.

Further, as we restrict to equal sized bid volumes we can formally describe the order book by a pair of two ordered vectors. This $(\mathbf{B}_t, \mathbf{S}_t)$ with $\mathbf{B}_t = (B_{t,1}, \dots, B_{t,M_t^B})$ for the buy side and $\mathbf{S}_t = (S_{t,1}, \dots, S_{t,M_t^S})$ for the sell side at time t with M_t and \bar{M}_t indicating the corresponding length. We sort \mathbf{B}_t increasingly and \mathbf{S}_t decreasingly so that $B_{1,t}$ is always the best (=cheapest) buy order and $S_{1,t}$ is the best (=most expensive) sell order. Obviously, it holds $B_{1,t} < S_{1,t}$ otherwise there would be a match with a corresponding trade. After the initialization at $t=0$ described above the \mathbf{B}_0 contains 18 orders and \mathbf{S}_0 contains 2 orders. Thus, the market clearing price of the day-ahead market is separating the buy and sell orders. *This method facilitated the accurate replication of the real order book mechanism.* Now, a crucial part of our model is the definition of the potential action times $\tau_{s,n}$. We assume that after evaluating a potential action of agent n the corresponding n -th agent determines its new potential action time. Thus, we do not allow that an action of other market participants triggers an adjustment of current potential action time. But, again this is plausible in efficient markets. Further, actions might also be triggered by external events $e_{1,n}, \dots, e_{E,n}$ relevant for the agent n , such as (partial) outages or forecast update times. Given time t we can define the next event after time t by.

$e_n(t) = \min\{e_{i,n} | e_{i,n} > t, i = 1, \dots, E\}$. Formally, we define the potential action time by

$$\tau_{s,n} = \min \{e_n(\tau_{s-1,n}), \tau_{s-1,n} + \delta_{s,n}\} \quad (1)$$

$$\delta_{s,n} = \begin{cases} \max \left\{ \frac{T - \tau_{s-1,n}}{q_{\tau_{s-1,n},n}^{\max} - q_{\tau_{s-1,n},n}}, \epsilon \right\}, & q_{\tau_{s-1,n},n}^{\max} > 0 \\ \max \left\{ \frac{T - \tau_{s-1,n}}{q_{\tau_{s-1,n},n}^{\min} - q_{\tau_{s-1,n},n}}, \epsilon \right\}, & q_{\tau_{s-1,n},n}^{\max} < 0 \end{cases} \quad (2)$$

for agent n , step s and tiny time $\epsilon > 0$. We choose $\epsilon = 0.01$. In addition we initialize $\tau_{0,n} = 0$ as time for the initial action. The fraction in (1) gets smaller if the nominator gets smaller, i.e. we are getting closer to delivery. This definition can be used to define the next potential action time at time t of agent n by

$$\tau_n(t) = \min \{ \tau_{s,n} | \tau_{s,n} > t, s = 0, 1, \dots \} \quad (3)$$

The corresponding vector $\tau(t) = (\tau_1(t), \dots, \tau_N(t))$ determines the next acting agent at time t . This is

$$n(t) = \arg \min_{n=1, \dots, N} \{\tau_n(t)\} \quad (4)$$

Thus, the agent $n(t)$ is checking for a potential action at time $\tau_n(t)$ and eventually performs an action. Afterwards, this agents computes her next potential action time by (1). *These specific formulas guide the entire algorithm to precisely recreate a continuous time frame, aligning with the needs of reality and avoiding any discrete time operations.* Now let us elaborate of the decision potential action and how the action changes the order book.

First, we remark that the action depends to some extent on the type of agent.

When a market player submits an order he decides if submitting a buy or a sell offers depending different factors: first of all, players aim at keep the position declared at the end of the day ahead market, so if they register an increasing (decreasing) of the energy production they will try so sell (buy) energy to fill the gap. Secondly, the type of order and the decision of submitting is depending on the marginal costs and on the current market price, if marginal costs are higher than the market price there is no reason to sell energy because the revenues will be lower than the production costs. Third, all agents submit trying to maximize their revenues. In addition, the submission decision varies according to the particular technology. Due to the fact that a wind power plant doesn't have production costs, if it forecasts a decrease of power production it will try to buy the gap of energy at the maximum price allows in the market P_{max} , on the other hand, when it forecasts an increase of production it will try to sell the surpluses at 0 €/MWh. In the event that the order doesn't find immediately a match, the wind agent retire the order from the order book to don't effectively buy energy at a high price or sell its production at 0 €/MWh. A thermal power plant submits orders always at its marginal costs MC , deciding to buy or sell the energy available depending on the current market price MP . If $MC > MP$ it tries to buy energy so it can keep its position buying energy at a cheaper price than its production price, while if $MC \leq MP$ it tries to sell energy increasing its revenues. The decision to buy or sell energy also affects the volumes q_n to trade and consequently the priority to make a decision a^n . For instance, a thermal power plant that has 20% of its maximum capacity left after the closing of the day-ahead market, it will decide to submit more (less) often if its marginal costs are higher (lower) than the market price. *This approach links market consequences to both external factors (power production forecasts associated with weather agents) and internal factors (market price dynamics).*

The market price at the beginning of the continuous trading coincides with the system marginal price coming from the day-ahead market result. So, all power plants that have been accepted in the day-ahead session could try to buy the quantity declared to sell previously if the match price of the transaction decrease during the intraday market, or they can sell the remain quantity if the transaction price of the matches increase. All power plants out of the day-ahead market can try only to sell energy at the beginning of the market and they can

turn into buyer agents only if they manage to sell a volume of energy and then the transaction market price becomes lower than their marginal costs.

Once the simulation starts, all thermal power plants submit an order to fill the order book. In particular all power plants accepted in the day-ahead market submit a buy order while the others submit a sell order. The last power plant accepted in the day-ahead market can decide if submitting a buy or sell order because its marginal costs are equal to the system marginal price. Every time a thermal agent got a match, it immediately submit an order in the opposite direction. For instance, if an agent n who sold (buy) energy gets a match, he immediately submits a buy (sell) order at the same price reduced (increased) by the transaction costs. This behavior is due to the fact that once an agent sells (buy) a quantity, it has immediately a quantity available to buy (sell).

The algorithm governing the formulation of agents' pricing strategies was crafted and developed using MATLAB. Simultaneously, the order book, designed to store and organize submitted offers, was implemented using the GO language. Seamless communication between these two algorithms is maintained throughout the simulation process.

3.1 Wind prevision

In this subsection, the mathematical formulas used to replicate wind power production forecasts $W_{t,i}$ at time t for agent i are reported. The $W_{t,i}$ might be interpreted as a matrix with N_{RES} rows and the number of previsions updates (T) columns. At the beginning of the session, every renewable agent i has initially expected power production $E[W_{0,i}] = \mu_{0,i}$ corresponding to the energy declared in the day ahead market. While at the end of the trading session, they will have a different power production $W_{T,i}$ with the same conditional expectation on the market opening, i.e. $E[W_{0,i}] = E[W_{T,i}|F_0]$. In particular, we assume for the first column of the matrix a multivariate distribution around the initial value $\mathbf{W}_0 = (W_{0,1}, \dots, W_{0,N})' \sim N_N(\boldsymbol{\mu}_0, \Sigma_0)$ with initial expectation $\boldsymbol{\mu}_0 = (\mu_{0,1}, \dots, \mu_{0,N})'$ and covariance matrix Σ_0 which describes the (usually) positive correlation between the wind farms.

During the trading session, we assume a specific mean reversion update for the wind information: For each time step t the expected power production $\mu_{t,i} = E[W_{T,i}|F_t]$ of the wind generators i is getting closer to the expected wind generation $\mu_{T,i} = E[W_{T,i}]$ at final time T . More precisely we choose.

$$W_{t,i} = \mu_{T,i} + \phi_t(W_{t,i} - \mu_{T,i}) + \varepsilon_{t,i}$$

with time-varying standard deviation of the innovation $\sigma_t = 2^{\sqrt{T-t}} + 2$, time-varying mean reversion

parameter $\phi_t = 1 - \sqrt{T-t} + 1$ and $\varepsilon_{t,i} \sim N_1(\mathbf{0}, \sigma_t)$. Thus, the mean reversion decreases ϕ_t and the standard deviation σ_t when getting closer to delivery T to map a more realistic setting. However, it is clear that the wind power process could be replaced by a more sophisticated process, especially those estimated from real data.

4 Results and discussion

In this section, the results obtained from one scenario simulation of the agent-based model are shown and discussed.

The analyzed scenario considers 10 wind and 20 thermal plants. The marginal costs and the maximum capacity of each technology are reported in Table 1

The simulation starts with the supply–demand curve resulting from the day-ahead market auction for initialization of the intraday market, see Figure 6. On the x-axes, the aggregated volume of each generator ordered from the cheapest to the most

Table 1 An example table of 30 agents

Agent ID	Type	Marginal costs [EUR/MWh]	Maximum capacity [MW]
1	Wind	0	50
2	Wind	0	110
3	Wind	0	76
4	Wind	0	51
5	Wind	0	112
6	Wind	0	169
7	Wind	0	94
8	Wind	0	68
9	Wind	0	87
10	Wind	0	186
11	Coal	20	71
12	Coal	40	191
13	Coal	60	50
14	Coal	80	177
15	Coal	100	117
16	Coal	120	78
17	Coal	140	60
18	Coal	160	54
19	Coal	180	93
20	Coal	200	126
21	Natural gas	19	163
22	Natural gas	38	164
23	Natural gas	57	195
24	Natural gas	76	135
25	Natural gas	95	79
26	Natural gas	114	167
27	Natural gas	133	181
28	Natural gas	152	129
29	Natural gas	171	74
30	Natural gas	190	135

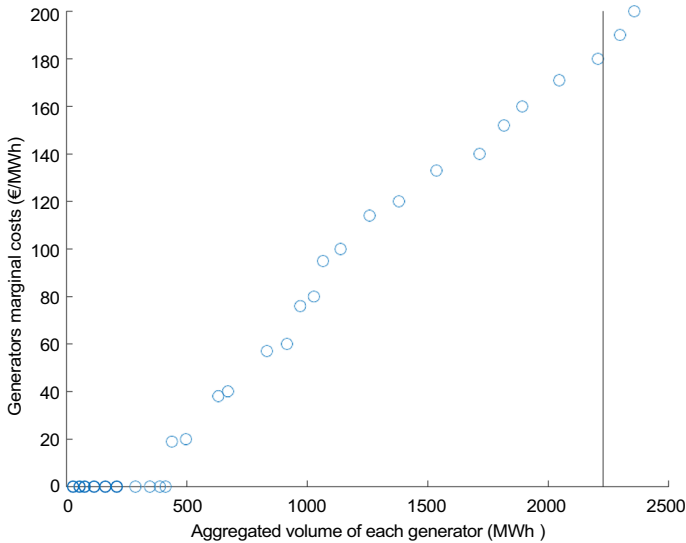


Fig. 6 Supply–demand curve as in the supply-stack model used for initialization

expensive and the total demand are represented, while in the y-axes there are the marginal costs for all generators. The intersection between the demand and supply curve delimits with generators have traded during the day-ahead market and which one is excluded, the corresponding y-value of the intersection point determines the system marginal price as well as the starting market price for the continuous ID market.

The last generator accepted in the day ahead market is the thermal 19, so thermal 20 and 30 are excluded and they didn't sell energy while the system marginal price is $P^0 = 180\text{€/MWh}$.

In Fig. 7 is presented the position of each generator at the end of the day ahead and at the beginning of the intraday market at $t=0$.

As already mentioned all accepted thermal power plants retain a small percentage of their total capacity to eventually sell it during the continuous trading. Wind power plants position corresponds to the power production forecast at $t = 0$. Once the ID market starts they forecast a new power production at any time stamp and consequently they try to sell or buy energy to maintain the initial position at the end of the continuous session. In Figure 8 the energy production forecast during the trading time-frame of each wind plant is reported.

At the beginning of the session all agents forecast a certain production but an increasing of wind energy during the day leads to raise the power forecast for almost all generators. This states that wind agents will try to sell the excesses of energy at P_{\min} , the most expensive thermal power plants will not sell energy and some of the thermal accepted in the day ahead market will reduce their production deciding to buy energy at a cheaper price instead of producing it. In Figure 9 the order book at each time stamp is represented combining with the match price trading.

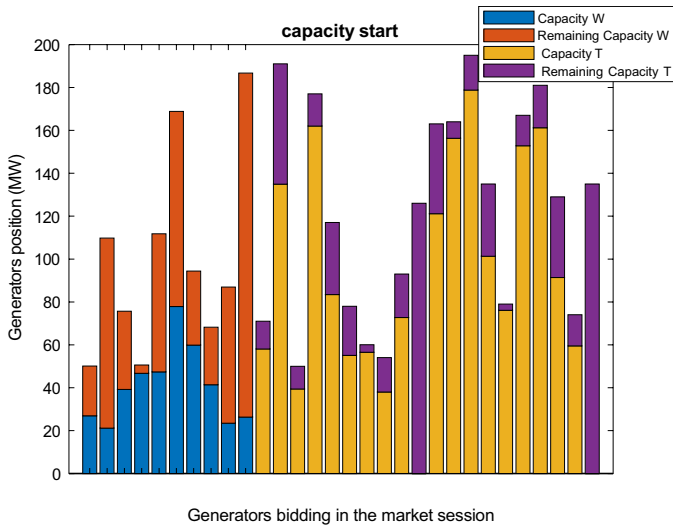


Fig. 7 Declared quantity at the end of the day-ahead market by each generator

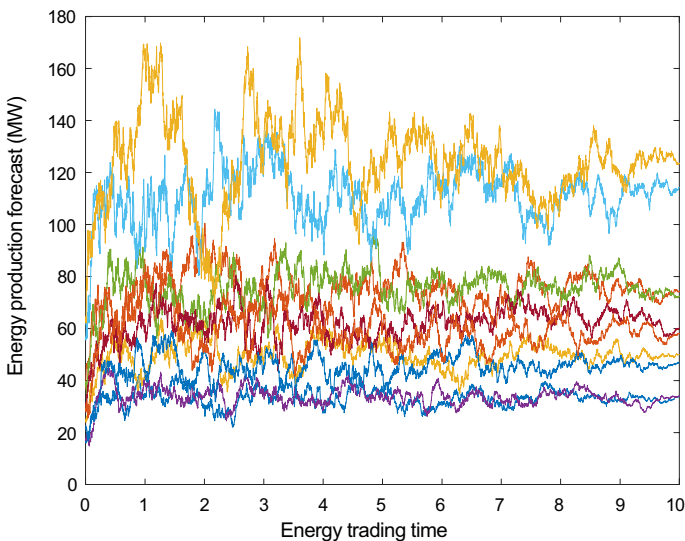


Fig. 8 Wind energy production forecast

The match curve starts from the initial market price and decrease after some hours as expected. The order book presents a bigger number of orders close to the delivery because agents that didn't manage to exchange their energy increase their action's frequency and since the market price is decreasing the thermal agents with high costs are able to buy energy at their marginal price. Figure 10 refers the position of each generator at the end of intraday market $t_f = T$.

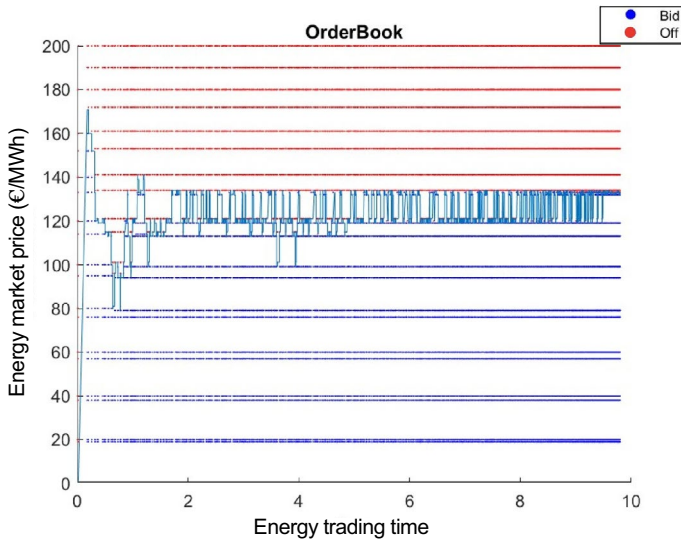


Fig. 9 Order book and match price trading

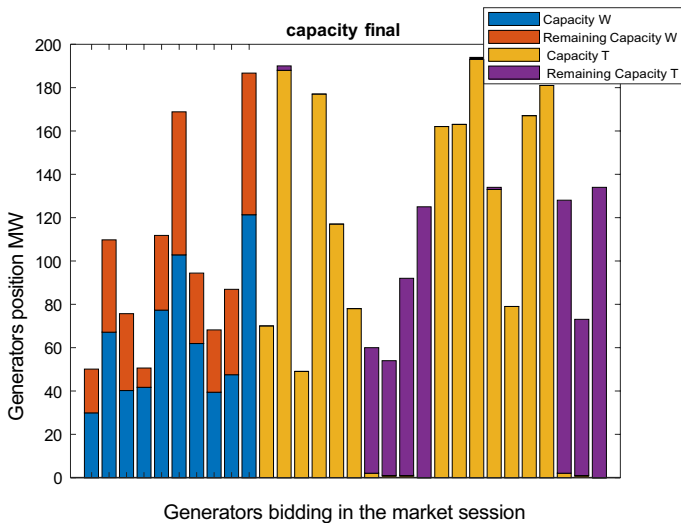


Fig. 10 Final production of each generator

As it was pointed out, wind power plants increase their production to sell energy to the most expensive thermal technologies that participated in the day ahead market. The previously excluded thermal power plants don't have any volume of energy to buy so they remain turn off while the thermal plants that have marginal costs lower than the market price manage to sell their entire capacity

successfully. To better understand the behavior of each market operator Figure 11 shows at which time stamp t an agent submit a bid and when it finds a match.

Each agent that find a match at every submission does not increase the action frequency like agent 11 and agent 21 that are the cheapest thermal power plants of the market. Agents that don't find a match increase their action frequency approaching the delivery time like agent 10 or 27. For instance, it is interesting to notice the behavior of agents 26 that at the beginning of the market tries to sell energy unsuccessfully but when the market price increase a bit he manages to sell at every action. Agent 16 is very active during the last 6 h of the market when the market price is around its marginal costs (120€/MWh) and 140€/MWh but it manages to sell all energy declared at the beginning of the ID market only during the last hour when the market price is stable around 140€/MWh.

4.1 Outages

It interesting is also to notice what happens in case of an outage of a thermal power plant. Herein one of the cheapest thermal plants with marginal costs of 40€/MWh faces an outage at hour 8, 2 h before the end of the delivery. Consequently, it turns from a seller to a buyer to avoid unbalances as shown in Figure 12.

Focusing on line 12, it can be noticed that after the outage, the thermal power plant strongly increases the number of actions trying to buy the energy it needs. Moreover, prices of energy increased and some players, like thermal 28, change their strategy of selling energy instead of buying it. In fact, thermal 28 marginal costs amount to 152€/MWh and the prices of the energy after the outage increase around 150 and 160 €/MWh as noticed in Figure 13.

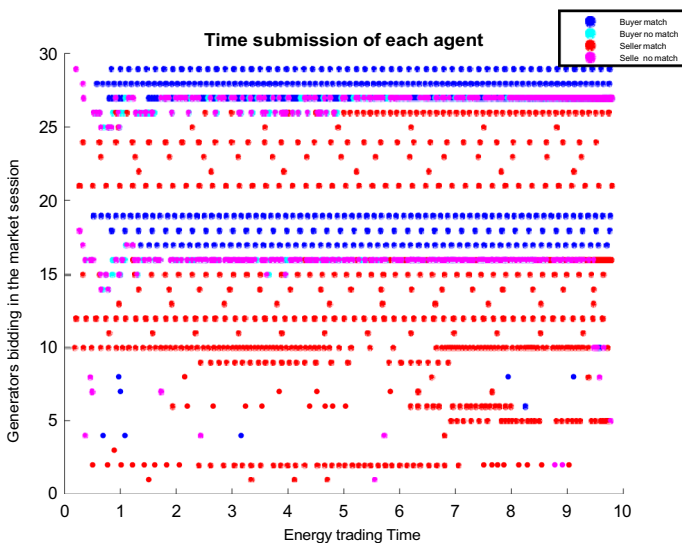


Fig. 11 Actions time of each agent

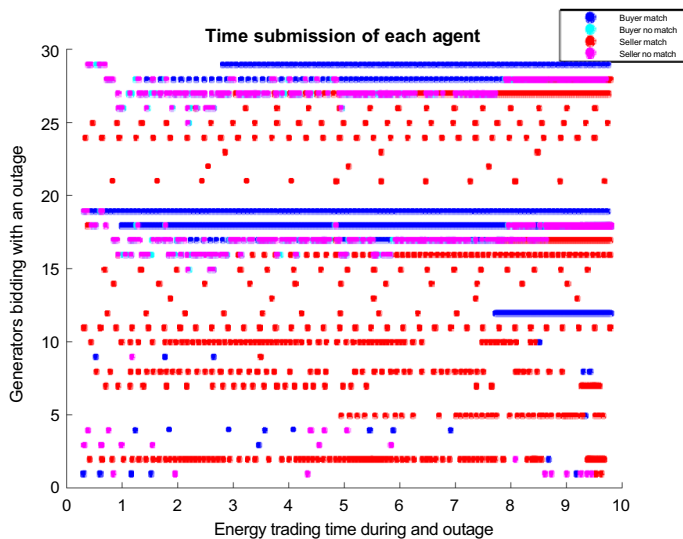


Fig. 12 Actions time of each agent after an outage

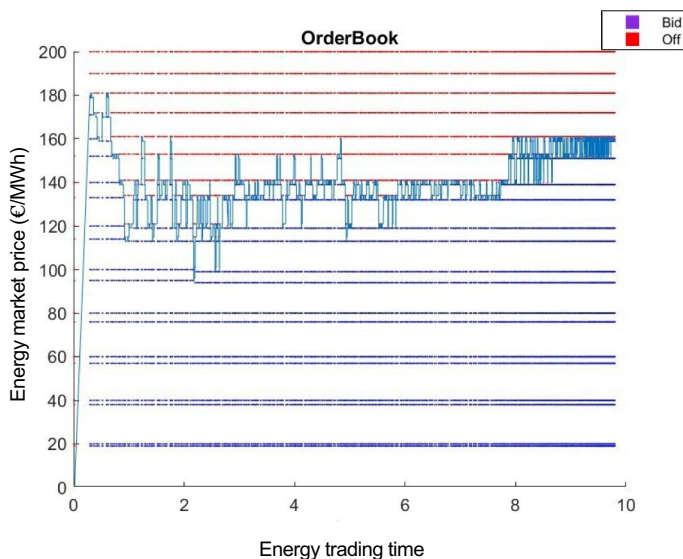


Fig. 13 Prices in the order book with an outage

5 Conclusion

This work develops an agent-based model able to simulate the continuous trading energy market limited to a bidding zone with thermal and wind power plants. Each agent can trade energy along a centralized order book able to store

and match all orders submitted. At each iteration, the order book is updated and orders are stored with a price-time merit order mechanism. Once a match occurs, the order book gives back the price and the quantity of the energy exchanged, and the market price is updated. Players are supposed to trade rationally aiming at maximizing their revenues and keeping their position balanced and two price strategies are carried out outlining thermal and wind power plants. Results show that the implemented algorithm replicates the main intraday continuous market characteristics highlighted by various statistical analyses of historical orders taken from the German, Spain and Italian ID markets. Starting from the results of the day-ahead market, the model first implements a function that performs the forecast of the wind power production and then studies the effect on prices and the agent's action. A fundamental role is playing the renewable energy capacity production and the thermal marginal costs. In a scenario in which the wind production increases, the most expensive thermal power plants turn off and buy the energy declared at the end of the day-ahead market from the wind plants that can sell at 0 €/MWh, while the cheapest power plants sell their entire capacity as long as their marginal costs are still lower than the market price. By contrast, if a decrease of wind production is registered, wind power plants will try to keep their position by buying energy from the thermal power plants and the market price increase significantly. Furthermore, the algorithm shows that the number of transactions increases approaching the real time delivery since players that did not find a match previously have to increase their number of submissions to sell or buy all energy needed. This also replicates the reality when players know better their position close to real-time and try to keep their position balanced submitting many orders. Additionally, the elaboration shows that in case of an outage of a thermal power plant, the price of energy increases significantly because agents suddenly need to buy the amount of energy previously declared at the end of the intraday market to not end the intraday session unbalanced. He increases her number of actions and other players characterized by higher marginal prices change their behavior trying to sell energy instead of buying it.

Researchers and professionals can utilize this model to explore diverse scenarios involving the integration of dispatchable and non-dispatchable power plants within a continuous trading energy market. Future research avenues may include the introduction of additional technologies such as batteries and hydro power plants. Moreover, incorporating an algorithm capable of replicating multiple zones could facilitate the study of potential congestion consequences.

Acknowledgements No particular acknowledgements has to be done for this work.

Authors contribution All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Andrea Alberizzi, Florian Ziel and Paolo Di Barba. The first draft of the manuscript was written by Andrea Alberizzi and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Funding Open access funding provided by Università degli Studi di Pavia within the CRUI-CARE Agreement. The authors did not receive support from any organization for the submitted work.

Data availability No data has been used for these works. The code used to lead the analyses can be shared if requested.

Declarations

Competing interests There are no competing of interest in this work.

Consent for publication All authors agreed with the content, they all gave explicit consent to submit, and they obtained consent from the responsible authorities at the institute/organization where the work has been carried out.

Consent to participate The study was approved by the university of Pavia and the university of Duisburg-Essen and it was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

1. Zweifel, Praktijnjo, Erdmann. energy in science and engineering energy economics- theory and applications. (2017)
2. Andreas Ehrenmann, Pierre Henneaux, Gerd Ku"pper, Johan Bruce, Bj"orn Klasman, and Linda Schumacher. The future electricity intraday market design. (2019)
3. New monthly record on epex intraday. <https://www.epexspot.com/en/news/new-monthly-record-epex-intraday>. Accessed: 5th Dec 2022
4. Haverbeke, D., Naesens, B., Vandorpe, W.: European energy markets and the new agency for cooperation of energy regulators. *J. Energy Nat. Resources L.* **28**, 403 (2010)
5. Leonardo Meeus Tim Schittekatte. The EU electricity network codes (2018)
6. Hirsch, Simon, Ziel, Florian: Simulation-based forecasting for intraday power markets: modelling fundamental drivers for location, shape and scale of the price distribution. *Energy. J.* **45**(3), 107–144 (2022)
7. Tobias Wittmann. Agent-based models of energy investment decisions. Springer Science & Business Media. (2008)
8. Ringler, P., Keles, D., Fichtner, W.: Agent-based modelling and simulation of smart electricity grids and markets—a literature review. *Renew. Sustain. Energy Rev.* **57**, 205–215 (2016)
9. [VBC+02] Thomas Veselka, Gale Boyd, Guenter Conzelmann, Vladimir Koritarov, Charles Macal, Michael North, Benjamin Schoepfle, Prakash Thimmapuram, et al. Simulating the behavior of electricity markets with an agent-based methodology: the electric market complex adaptive systems (emcas) model. Vancouver, Canada, (2002)
10. George Grozev, David Batten, Miles Anderson, Geoff Lewis, John Mo, Jack Katzfey. Nemsim: agent-based simulator for australia's national electricity market. In: *SimTecT 2005 conference proceedings*, (2005)
11. Deddy Koesrindartoto, Junjie Sun, and Leigh Tesfatsion. An agent-based computational laboratory for testing the economic reliability of wholesale power market designs. In: *IEEE power engineering society general meeting, 2005*, pages 2818–2823. IEEE, (2005)

12. Gode, Dhananjay K., Sunder, Shyam: Allocative efficiency of markets with zero-intelligence traders market as a partial substitute for individual rationality. *J. political econ.* **101**(1), 119–137 (1993)
13. Toft, I.E., Bagnall, Anthony J.: Adaptive sniping for volatile and stable continuous double auction markets. In: *Agent-Mediated Electronic Commerce and Trading Agent Design and Analysis*, pp. 119–134. Springer, Cham (2007)
14. Dave Cli. Minimal-intelligence agents for bargaining behaviors in market-based environments. Hewlett-Packard Labs Technical Reports (1997)
15. Gerald Tesauro and Jonathan L Bredin. Strategic sequential bidding in auctions using dynamic programming. In: *proceedings of the first international joint conference on Autonomous agents and multiagent systems: part 2*, pages 591–598, (2002)
16. Daniel Snashall, Dave Cliff. Adaptive-aggressive traders don't dominate. In: *international Conference on Agents and Artificial Intelligence*, pages 246–269. Springer, (2019)
17. Inman, Rich H., Pedro, Hugo TC., Coimbra, Carlos FM.: Solar forecasting methods for renewable energy integration. *Prog. energy combust. sci.* **39**(6), 535–576 (2013)
18. Henry Martin, Scott Otterson. German intraday electricity market analysis and modeling based on the limit order book. In: *2018 15th international conference on the European energy market (EEM)*, pages 1–6. IEEE, (2018)
19. Boukas, Ioannis, Ernst, Damien, Th'eate, Thibaut, Bolland, Adrien, Huynen, Alexandre, Buchwald, Martin, Wynants, Christelle, Corn'elusse, Bertrand: A deep reinforcement learning framework for continuous intraday market bidding. *Machine Learn.* **110**, 2335–2387 (2021)
20. Calvillo, C.F., S'anchez-Miralles, Alvaro, Villar, Jos'e, Mart'ın, F.: Optimal planning and operation of aggregated distributed energy resources with market participation. *Appl. Energy* **182**, 340–357 (2016)
21. Aaron Praktiknjo Peter Zweifel and Georg Erdmann. *Energy economics: theory and applications*. Springer, (2017)
22. Karsten Neuhoﬀ, Nolan Ritter, Aymen SalahAbou-El-Enien, Philippe Vassilopou- los. Intraday markets for power: discretizing the continuous trading? Working papers EPRG 1609, Energy Policy Research Group, Cambridge Judge Business School, University of Cambridge, (2016)
23. New monthly record on epex intraday. <https://www.epexspot.com/en/regulation>. Accessed: 15th Dec 2022
24. Nemo committee. Continuous trading matching algorithm. <https://www.nemo-committee.eu/assets/files/continuous-trading-matching-algorithm.pdf>
25. Andrea Alberizzi, Alessandro Zani, Paolo Di Barba, Milo's Panto's. Statistical analysis of two different intraday market designs: the german and iberic intra-day market. In: *2022 18th International Conference on the European Energy Market (EEM)*, pages 1–6, (2022)
26. Narajewski, M.-I, Ziel, F.: Ensemble forecasting for intraday electricity prices: simulating trajectories. *Appl. Energy* **279**, 115801 (2020)
27. Marczasz, Grzegorz, Uniejewski, Bartosz, Weron, Rafal-: Beating the na'ive—combining lasso with na'ive intraday electricity price forecasts. *Energies* **13**(7), 1667 (2020)
28. Narajewski, M.-I, Ziel, F.: Optimal bidding in hourly and quarter-hourly electricity price auctions: trading large volumes of power with market impact and transaction costs. *Energy Econ.* **110**, 105974 (2022)
29. Gjerstad, S., Dickhaut, J.: Price formation in double auctions. *Games Econom. Behav.* **22**(1), 1–29 (1998)

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.